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Parametric Optimizing Green Sand-Casting Process Parameters using hybrid Taguchi Grey Relational Analyses and Principal Component Analyses

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ABSTRACT

The Green Sand-casting technique is a very ancient method of casting that has many different uses. The increased rate of errors and rejection in this process is a key drawback that reduces output and profits. It's challenging to develop a good link between the many different parameters and defects since the process is so complicated. This article describes a hybrid approach to find the co-relation for sand casting process's variables. This approach mixes the Taguchi method (TM) with Grey Relational Analysis (GRA) paired with Principal Component Analysis (PCA). Moisture content, Permeability, Loss of Ignition, Pouring Time & Pouring Temperature selected as input parameters while types of defects (Shrinkage, Blow holes, Cracks, Porosity) as responses for proposed study. The L27 OA from Taguchi is used to plan the tests. TM implemented to analyse individual responses. GRA is applied to find optimal solutions for a set of replies, whereas PCA is used to determine how much weight each response should be given. Using proposed methodology, 4% moisture content, 160% permeability, 5% loss of ignition, 60 seconds of pouring time, and 1400°C found as optimum set of parameters. The findings demonstrate that the hybrid approach, which makes use of both a cost-effective and efficient experimental design strategy, was successful in resolving the complexity trade-off experienced throughout the judgment process of multi-response optimization.

Keywords: Green sand-casting; process parameters; TM; GRA; PCA

INTRODUCTION

This method of sand casting has been refined over many years, and it is now capable of a wide range of uses in the metal casting industry. With developments in the process, sand-casting has emerged as the first option in many industrial applications since it is one of the most readily understood and extremely versatile processes. It's also understood that low-cost, defect-free casting production is essential. The goal of these efforts is to develop a technological remedy that will reduce the prevalence of casting flaws and enhance the sand-casting procedure. In order to reduce these flaws as much as possible, several factors of the sand-casting process are highlighted.

In his book "The Fifth Discipline," published in 1991, Genichi Taguchi outlined the principles of resilient design that might boost a process's output, dependability, and capacity to be mass-produced (Kackar 1985). The Taguchi method (Taguchi and Phadke 1986) is a systematic process used in resilient design that relies on well-orchestrated experimental data for meaningful analysis and objective inferences.

Squeeze casting process parameters were improved using TM by Arulraj, Palani, and Sowrirajan 2021, whereas manufacturing process parameters were optimized using TM and hybrid TM to increase component quality in a review by Rathi, Punjabi, and Jain 2016. Authors conclude that the TM is an effective problem-solving tool for increasing result, efficiency, and output rate in manufacturing processes. With the use of near net structured selective laser melting (SLM) technology, Sheshadri et al. 2021 were able to create high-quality components out of the nickel-based composite Inconel 625 (IN625). The Taguchi approach was used to systematically investigate, examine, and optimize the relevant variables.

Deng's Grey System theory, developed in 1982, is concerned with making choices based on incomplete data. Grey information is defined as that which falls between the two extremes of known and unknown data. Complex problems with critical data are ideal candidates for the use of Grey System theory. In order to solve complicated systems, the most common quantitative and systematic technique is grey connection analysis, a subsystem of grey system theory (Patil, Walke, and Gawkhare 2019).

Electrochemical machining of EN-31 steel utilizing GRA is studied by Chakradhar 2011, who look at the impact and parametric optimization of processing parameters. Included as well is a presentation (Raykar, D'Addona, and Mane 2015) on their research into high-speed turning with Al 7075, a high-strength aluminum alloy with aerospace applications.

Dimensionality reduction methods, such as PCA, may substantially simplify and enhance process monitoring by projecting the results into a lesser space that properly reflects the status of system. PCA is a multidimensional space shrinking method. The association structure in between process variables is preserved as a reduced dimensional representation is generated. The traditional PCA indices are replaced with metric distances produced using the self-organization mapping (SOM) technique, as described in the study by Bouhouche, Yahi, and Bast 2011. SOM, traditional PCA, and a PCA-SOM hybrid are compared and contrasted in this research.

Kuo, Huang, and Yang 2021, employed fusion of TM as well as PCA for the process parameter optimization of melt spinning process. In their work, Chandrashekarappa et al. 2021 machine hard steel using EDM with a variety of electrodes with dielectric fluids. Author owes a debt of gratitude to qazi2021experimental, for their insightful addition to our knowledge of machining specifications. Using a Taguchi OA mixed design (L16), SN ratios, ANOVA, & PCA, authors analyzed and adjusted the lubrication strategies used for milling AA5005-H34. There is substantial agreement between the acquired findings and those reported in the scholarly literature.

A. Kumari et al. 2020 describe a novel method for optimizing the process parameters of a green sand mould using a multi-response orthogonal array and grey relational analysis. Authors demonstrate GRA's potential in effectively optimizing input process parameters for diverse response characteristics. Shilpa, Prakash, and Shivakumar 2020 devised a method that combines the techniques of theoretical modelling (TM) and generalized additive modeling (GRA) with regression analyses (RA) to improve the quality of green sand used in the sand mould. For the purpose of demonstrating the effects of Wire Electric Discharge Machining (WEDM) variable affecting Material removal rate (MRR) as well as surface roughness (Ra) for the recently created Magnesium metal matrix composite, Kavimani, Soorya Prakash, and Thankachan 2019 presented a test examination and inquiry.

The influence of plasma arc cutting (PAC) settings on the cut quality features of Inconel 625 alloy is the topic of Pothur, Ganesan, and Aruna 2020. research. Taguchi designs with L18 orthogonal arrays are developed using the DOE method. When it comes to achieving the ideal cutting circumstances, the GRA method is where it's at. To determine how input parameters (transverse speed, standoff distance, and water pressure) affect the output response and hence the best control factor, Kavimani et al. 2020 used Taguchi coupled grey relation analysis. The findings show that the output response is primarily affected by the stand-off distance and transverse speed.

Maximum weld hardness and minimum weld width and dilution were priorities for Saha and Majumder 2020 in their quest to improve weld quality and productivity. To identify the most crucial parameters for the welding process, a multi-attribute optimization was carried out utilizing a GRA and PCA hybrid strategy. It was also determined that the GRA plus PCA technique is a solid method for solving the multi-attribute optimization issue. Sutono et al. 2017 introduced a hybrid approach to identifying the optimal mix of product form characteristics for Kansei Engineering (KE). The proposed approach combines the TM plus GRA with principal component analysis. A case study was utilized to show how this technique may be put to use in maximizing the various Kansei reactions of a car's form design. The multi-response optimization decision-making complexity trade-off was resolved using this hybrid approach in KE.

When it comes to optimizing for multiple responses, the Taguchi technique on its alone is insufficient, as Zaman, Saha, and Dhar 2020 point out. To get over this difficulty, GRA may be combined with TM such that the grey relational grade (GRG) of the whole process is determined and then utilized to optimize the parameters according to Taguchi's S/N ratio. Utilizing PCA, one can ascertain the relative weight of each answer, which allows for more precise calculation of GRG as a whole. Viswanathan et al. 2020 studied the effects of dry circumstances on the cutting force (Fz), tool flank wear (VB), and surface roughness (Ra), material removal rate (MRR), while turning a magnesium alloy with a PVD-coated carbide insert. The experiments were conducted using Taguchi's L27 orthogonal array. Authors have used a mixed approach combining PCA and generalized estimating equations (GRA) to determine the best parameters to use. Taguchi technique was used in trials, statistical analysis, and optimizing individual responses by Chate et al. 2018. To balance competing demands from various objective functions in a process, GRA is used with principal component analysis.

In their study, Nanang Qosim et al. 2020, observed effect of moisture content on the green sand casting defects.

Through this research, Kavimani et al. 2022 suggest a technique that combines the Taguchi approach with the GRA, which is then connected with principal component analysis. For the purpose of assessing and approximating the impact of machining parameters on the response variables of Wire Electrical-Discharge Machining (WEDM) carried out on a Magnesium-based metal matrix composite, this technique has been employed.

By using GRA in conjunction with the PCA approach, Jagadish and Ray 2016 have been able to design a method that has optimized the process variables of environmental electrical discharge machining (EDM).

Numerous researchers used the fever input factors for the minimization of one or two defects using either TM, GRA, or PCA, as outlined from the aforementioned study. According to the author's understanding, no one has attempted to create casings without defects.

Literature review guided towards the selection of combination of such input parameters with their levels, optimization using hybrid TGRA-PCA methods that can ensure defect free casting.

EXPERIMENTAL PROCESS

The proposed study makes use of information gathered from foundry (Figure 1 (a, b, c)). Based on in-depth literature review and discussion with senior personals of foundry and as per their suggestions input parameters and levels are selected. Table 1 displays the five process parameters and their associated levels that will be used in subsequent analysis. The inquiry was carried out using a Taguchi L27 orthogonal array (Table 2), and the outcomes for green sand-casting variables are shown in Table 3.

For the proposed study, Grey Cast Iron, ASTM A48 Class 30 material used with part specifications as Mass: 6800-7800 kg/m^3, UTS: 395 MPa, Modulus of Elasicity: 124 GPa. Specification of sand as GFN: 70, Specific Gravity: 2.39-2.55, Absorption, %: 0.45, Moisture Content, %: 0.1-10.1.

Pyrometer was used for Temperature measurement at the time of pouring.

The experiment described above was devised and carried out with the assistance of Minitab-2019 software.

METHODOLOGY ADOPTED

TAGUCHI METHOD

Entire study divided in two phases, in first phase individual response analyzed using TM, and find out the optimum set of parameters.

In the second phase Taguchi based GRA and PCA used to analyzed all responses simultaneously and find out optimum parameters, as discussed below.

TAGUCHI BASED GRA

1. Determine the Signal-to-Noise Ratio

Calculations of the signal-to-noise ratio (S/N ratio) are performed in order to analyze the quality of experiment.

In terms of the S/N ratio (larger is better):

$$\left(\frac{S}{N}\right)_i = -10log\left[\frac{1}{n}\sum_{j=1}^{n}\frac{1}{Y_{ij}^2}\right] \tag{1}$$

S/N ratio (Smaller the better characteristic):

$$\left(\frac{S}{N}\right)_i = -10log\left[\frac{1}{n}\sum_{j=1}^{n}y_{ij}^2\right] \tag{2}$$

S/N ratio (Nominal the best characteristic):

$$\left(\frac{S}{N}\right)_i = -10log\left(\frac{\bar{y}^2}{\bar{s}^2}\right) \tag{3}$$

where, i is the number of trials; y_{ij} is the quality characteristic measured value for the ith trial and jth experiment; and n is the number of repetitions for the experimental combination.

2. Making the Determination Matrix

$$\begin{bmatrix} X_{11} & X_{12} & \dots & X_{1n} \\ X_{21} & X_{22} & \dots & X_{2n} \\ \dots & \dots & \dots & \dots \\ X_{m1} & X_{m2} & \dots & X_{mn} \end{bmatrix} \tag{4}$$

3. Data Processing

If the target values of original sequences is infinite, then it has a characteristic of the "Higher is Better". The original sequences can be normalized a follow:

$$X_i^* = \frac{X_i^0(k) - minX_i^0(k)}{maxX_i^0(k) - minX_i^0(k)} \tag{5}$$

When the "Lower is Better" is a characteristic of the original sequence, then the original sequence should be normalized as follows:

$$X_i^* = \frac{maxX_i^0(k) - X_i^0(k)}{maxX_i^0(k) - minX_i^0(k)} \quad (6)$$

4. The Grey Relational Coefficient and Its Calculation.

$$\zeta_i(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{oi}(k) + \zeta\Delta_{max}} \quad (7)$$

ζ= Identification Coefficient; $0 \leq \zeta \leq 1$

5. Compute the Relative Value of Grey Relational Grade.

$$\gamma_i = \frac{1}{n}\sum_{j=1}^{n} \beta_j \zeta_i(k) \quad (8)$$

β_j= Weight for each process parameter.

PCA

PCA done using Minitab program. The values of Grey Relational Coefficients for all four flaws are input. And the results are tabulated. The Grey Relational Analyses will make use of the distinct fault weights, since they are clearly different for the four flaws.

RESULT & DISCUSSION

In present study five process parameters & four defects of green-sand casting considered for optimization based on literature review and discussion with foundry personals.

As discussed, first individual responses were analyzed and optimum parameters identified.

The images of all four responses are shown in Figure 8(a, b, c, d).

As shown in Table 8, as details available from the foundry, defective components observed as 40.71% while rejection of the components recorded as 9.28%.

From the analyses of individual response, it is clear that, for shrinkage and blow holes, Pouring Time is the most influenced parameter while for cracks pouring temperature and for porosity Loss of Ignition having highest impact. The same outcome also confirm by Aloni 2019, A. Kumari et al. 2020.

The combined Taguchi-GRA-PCA approach is used to determine the best possible combination of a green sand-casting process's parameters.

Casting imperfections have 'lower the better' performance features. The experimental conclusions documented in Table 2 were substituted in Eq. 2.

Table 3, shows observed defects and S/N ratio. Eq. 7 used to find the normalized values which are shown in Table 4.

The Outcomes obtainable in Table 4 were substituted in Eq. 7 to approximate GRCs of all four defects which are shown in Table 5.

PCA was implemented to outline the weighting values (Table 6). The contributions of shrinkage, Blowholes, cracks & Porosity are 0.49703, 0.49844, 0.00168 and 0.00194 respectively. PCA-GRGs were calculated as shown in Table 5.

Figure 8 displays the PCA-GRG graph, which shows that, the finest combination of the green sand-casting process variables is the set with A2 (Moisture content), B3 (Permeability), C1 (Loss of Ignition), D3 (Pouring Time), E3 (Pouring Temperature).

CONCLUSION

The current study's objective is to reduce errors in green sand castings in order to boost their quality and efficiency. To identify the most crucial +parameters for the green sand-casting process, a multi-attribute optimization based on a GRA/PCA hybrid strategy has been carried out.

The outcomes of this study are as follows:

1. Individual defects were examined in the first step, and the best settings were found for each.
2. For shrinkage, the ideal set of specifications were found as having a moisture content of 5%, a permeability of 130%, a loss of ignition rate of 7%, a pouring time of 50 seconds, and a pouring temperature of 1375°C (Figure 2, Table 7).
3. Moisture Content 5%, Permeability 100%, Loss of Ignition 7%, Pouring Duration 50 sec., and Pouring Temperature 1375°C were found to be the best combination of specifications for blow holes (Figure 3, Table 7).
4. It was determined that the ideal set of specifications for cracks was moisture content of 3%, permeability of 130%, loss of ignition of 5%, pouring time of 50 seconds, and pouring temperature of 1350°C (Figure 4, Table 7).
5. The ideal set of specifications for porosity was determined to be moisture content of 4%, permeability of 100%, loss of ignition of 6%, pouring time of 60 seconds, and pouring temperature of 1350°C (Figure 5, Table 7).
6. Multi-attribute optimization problems are well-suited to the GRA and PCA technique.
7. To calculate the relative importance of different quality features, the PCA method is used with great success.
8. The optimal values for the other process parameters were also determined to be 4% moisture content, 160% permeability, 5% loss of ignition, 60 sec. of pouring time, and 1400°C (Figure 6).

9. Table 8 interprets response table for PCA-GRG, shows that Pouring Time has highest impact on the results followed by Pouring Temp., Loss of Ignition, Moisture Content and Porosity.

Compared to the analyses of individual response done by TM which provides optimum set of parameters for the particular response, the proposed novel hybrid technique provided combined analyses of all responses simultaneously and suggest a set of optimum parameters. Mapping of research title, objective, methodology and conclusion shown in Figure 9.The findings of current study will provide foundry owners with valuable direction for boosting product quality involving the casting of green sand by identification of optimum set of parameters for the defect's minimization.

TABLE 1. Process parameters with levels

Process Parameters	Level-1	Level-2	Level-3
Moisture Content (%)	3	4	5
Permeability (%)	100	130	160
Loss of Ignition	5	6	7
Pouring Time (°C)	40	50	60
Pouring Temperature (Sec)	1350	1375	1400

TABLE 2. L27 Orthogonal Array

Moisture Content	Permeability	Loss Of Ignition	Pouring Time	Pouring Temperature
3	100	5	40	1350
3	100	5	40	1375
3	100	5	40	1400
3	130	6	50	1350
3	130	6	50	1375
3	130	6	50	1400
3	160	7	60	1350
3	160	7	60	1375
3	160	7	60	1400
4	100	6	60	1350
4	100	6	60	1375
4	100	6	60	1400
4	130	7	40	1350
4	130	7	40	1375
4	130	7	40	1400
4	160	5	50	1350
4	160	5	50	1375
4	160	5	50	1400
5	100	7	50	1350
5	100	7	50	1375
5	100	7	50	1400
5	130	5	60	1350
5	130	5	60	1375
5	130	5	60	1400
5	160	6	40	1350
5	160	6	40	1375
5	160	6	40	1400

TABLE 3. Observed Defects and S/N ratio

Trial No.	Shrinkage	SNR SH	Blow Holes	SNR BH	Cracks	SNR CR	Porosity	SNR PO
1	16.7	-24.45433	16.8	-24.50619	14.5	-23.22736	15.9	-24.02794
2	15.2	-23.63687	14.3	-23.10672	13.8	-22.79758	17	-24.60898
3	20	-26.02060	21.2	-26.52672	17.3	-24.76092	15.1	-23.57954
4	12.3	-21.79810	13.1	-22.34543	12.3	-21.79810	11.3	-21.06157
5	14.7	-23.34635	14.9	-23.46373	11.8	-21.43764	12.9	-22.21179
6	14.8	-23.40523	15.1	-23.57954	19.2	-25.66602	17.2	-24.71057
7	19.4	-25.75603	18.5	-25.34343	15.2	-23.63687	16.4	-24.29688
8	12.5	-21.93820	12.3	-21.79810	16.7	-24.45433	18.2	-25.20143
9	17.8	-25.00840	17.2	-24.71057	18.5	-25.34343	15	-23.52183
10	19.5	-25.80069	19.1	-25.62067	19.1	-25.62067	5	-13.97940
11	16.7	-24.45433	15.9	-24.02794	14.9	-23.46373	16	-24.08240
12	15.5	-23.80663	13.9	-22.86030	16.7	-24.45433	8	-18.06180
13	13.4	-22.54210	14.5	-23.22736	18.4	-25.29636	11.9	-21.51094
14	16.9	-24.55773	17.7	-24.95947	16.2	-24.19030	12	-21.58362
15	18.7	-25.43683	19	-25.57507	12.7	-22.07607	18.3	-25.24902
16	18.2	-25.20143	17.6	-24.91025	11	-20.82785	17.5	-24.86076
17	16.1	-24.13652	15.8	-23.97314	16.2	-24.19030	13.4	-22.54210
18	12.5	-21.93820	13.2	-22.41148	14.9	-23.46373	14.2	-23.04577
19	11.9	-21.51094	12	-21.58362	14.2	-23.04577	13.2	-22.41148
20	10.8	-20.66848	11.5	-21.21396	17.5	-24.86076	16.1	-24.13652
21	17.6	-24.91025	18.1	-25.15357	16.9	-24.55773	17.2	-24.71057
22	18.1	-25.15357	18.5	-25.34343	12.8	-22.14420	16.8	-24.50619
23	19.9	-25.97706	18.7	-25.43683	14.7	-23.34635	14.9	-23.46373
24	12.8	-22.14420	14.6	-23.28706	15.3	-23.69383	15.8	-23.97314
25	16.4	-24.29688	17.5	-24.86076	12.6	-22.00741	13	-22.27887
26	15.3	-23.69383	14.5	-23.22736	18.2	-25.20143	16.4	-24.29688
27	17.4	-24.81098	17.2	-24.71057	17.1	-24.65992	15.9	-24.02794

TABLE 4. Normalized responses value

Trial No.	Shrinkage (%)	Blow Holes (%)	Cracks (%)	Porosity (%)
1	0.70736	0.61968	0.49595	0.89165
2	0.55462	0.35627	0.40712	0.94321
3	1.00000	1.00000	0.81292	0.85186
4	0.21106	0.21297	0.20054	0.62843
5	0.50034	0.42347	0.12604	0.73049
6	0.51134	0.44526	1.00000	0.95222
7	0.95057	0.77728	0.58060	0.91551
8	0.23724	0.10995	0.74956	0.99578
9	0.81088	0.65815	0.93332	0.84674
10	0.95891	0.82946	0.99063	0.00000
11	0.70736	0.52967	0.54481	0.89648
12	0.58634	0.30988	0.74956	0.36225
13	0.35007	0.37897	0.92359	0.66830

continue ...

... cont.

14	0.72668	0.70500	0.69498	0.67475
15	0.89093	0.82088	0.25799	1.00000
16	0.84694	0.69574	0.00000	0.96555
17	0.64797	0.51935	0.69498	0.75980
18	0.23724	0.22540	0.54481	0.80450
19	0.15741	0.06958	0.45842	0.74821
20	0.00000	0.00000	0.83356	0.90128
21	0.79254	0.74154	0.77093	0.95222
22	0.83800	0.77728	0.27208	0.93409
23	0.99187	0.79486	0.52055	0.84158
24	0.27573	0.39021	0.59237	0.88679
25	0.67794	0.68642	0.24380	0.73645
26	0.56526	0.37897	0.90397	0.91551
27	0.77399	0.65815	0.79205	0.89165

TABLE 5. Grey Relational coefficient & PCA-GRG

	Grey Relational Coefficient				PCA-GRG
Trial No.	Shrinkage (%)	Blow Holes (%)	Cracks (%)	Porosity (%)	
1	0.63080	0.56798	0.49798	0.82189	0.14977
2	0.52889	0.43717	0.45751	0.89800	0.12082
3	1.00000	1.00000	0.72772	0.77144	0.24955
4	0.38792	0.38849	0.38478	0.57368	0.09705
5	0.50017	0.46445	0.36391	0.64977	0.12049
6	0.50574	0.47405	1.00000	0.91278	0.12278
7	0.91003	0.69183	0.54383	0.85545	0.19993
8	0.39596	0.35970	0.66627	0.99162	0.09478
9	0.72556	0.59393	0.88234	0.76539	0.16491
10	0.92406	0.74567	0.98160	0.33333	0.20831
11	0.63080	0.51529	0.52345	0.82847	0.14321
12	0.54725	0.42013	0.66627	0.43946	0.12084
13	0.43481	0.44602	0.86744	0.60118	0.11026
14	0.64656	0.62893	0.62110	0.60588	0.15927
15	0.82092	0.73624	0.40257	1.00000	0.19440
16	0.76563	0.62169	0.33333	0.93554	0.17320
17	0.58684	0.50987	0.62110	0.67550	0.13704
18	0.39596	0.39228	0.52345	0.71890	0.09865
19	0.37241	0.34955	0.48004	0.66508	0.09036
20	0.33333	0.33333	0.75026	0.83512	0.08368
21	0.70675	0.65923	0.68580	0.91278	0.17070
22	0.75529	0.69183	0.40719	0.88353	0.18066
23	0.98399	0.70907	0.51049	0.75940	0.21121
24	0.40841	0.45054	0.55088	0.81538	0.10752
25	0.60823	0.61457	0.39803	0.65483	0.15264
26	0.53491	0.44602	0.83889	0.85545	0.12281
27	0.68870	0.59393	0.70626	0.82189	0.16028

TABLE 6. PCA analyses of results

Eigen Vectors					
Variable	PC1	PC2	PC3	PC4	Contribution
Shrinkage (%)	0.70500	0.05300	0.00100	0.70700	0.49703
Blow Holes (%)	0.70600	0.03300	0.00200	-0.70700	0.49844
Cracks (%)	-0.04100	0.70600	-0.70700	-0.01100	0.00168
Porosity (%)	0.04400	-0.70500	-0.70700	0.00900	0.00194

TABLE 7. Optimum Values of individual Input Parameters

Defects	Optimum Input Parameters and values				
	Moisture Content	Permeability	Loss of Ignition	Pouring Time	Pouring Temp.
Shrinkage	5%	130%	7%	50 sec.	1375°C
Blow Holes	5%	100%	7%	50 sec.	1375°C
Cracks	3%	130%	5%	50 sec.	1350°C
Porosity	4%	100%	6%	60 sec.	1350°C

TABLE 8. Rejection Summary (Courtesy: Hariom Metal Cast, Bhavnagar)

Sr No	Casting Name/ No	Number of Parts Checked	Number of Defective parts	No of Rejected parts	Rejection (%)
1	101	10.0	4.0	1.0	10.0
2	102	10.0	5.0	1.0	10.0
3	104	10.0	4.0	1.0	10.0
4	105	10.0	4.0	1.0	10.0
5	108	10.0	3.0	0.0	0.0
6	110	10.0	4.0	0.0	0.0
7	111	10	5	2	20.0
8	115	10	4	1	10.0
9	117	10	5	2	20.0
10	118	10	3	1	10.0
11	119	10	4	1	10.0
12	120	10	3	0	0.0
13	123	10	5	1	10.0
14	125	10	4	1	10.0
	TOTAL	140.0	57.0	13.0	9.2857

TABLE 8. Response Table for PCA-Grey Relational Grade

Level	Moisture Content	Loss of Ignition	Pouring Time	Pouring Temp.
1	-17.1	-16.36	-16.3	-16.76
2	-16.76	-17.35	-18.58	-17.84
3	-17.33	-17.47	-16.3	-16.58
Delta	0.57	1.11	2.29	1.26
Rank	4	3	1	2

(a) (b) (c)

FIGURE 1. (a) Mould Preparation at foundry, (b) Defective Housing at foundry, (c) Defective Levers at foundry

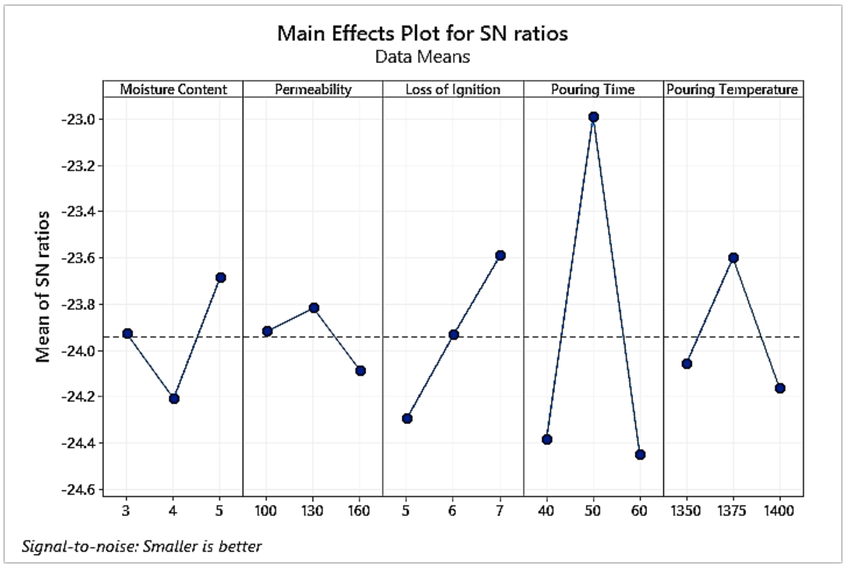

FIGURE 2. Main Effect Plot for Shrinkage

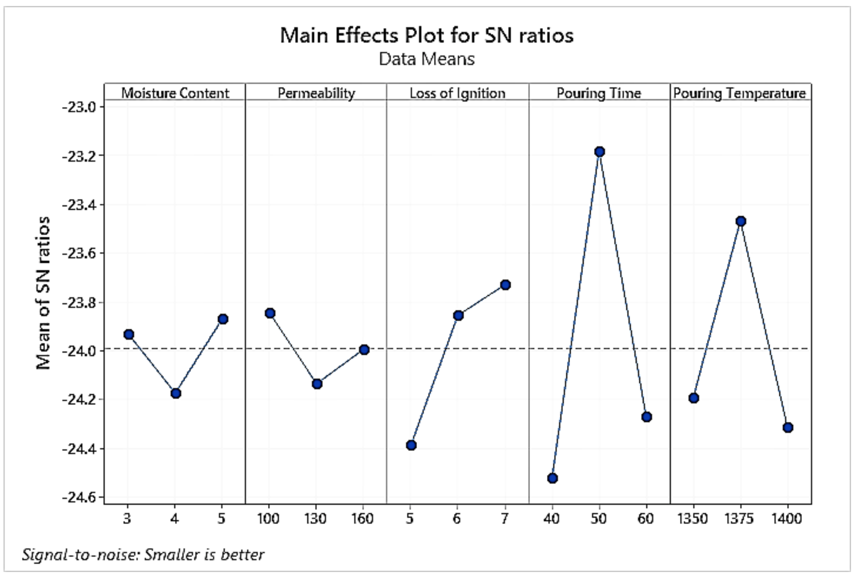

FIGURE 3. Main Effect Plot for Blow Holes

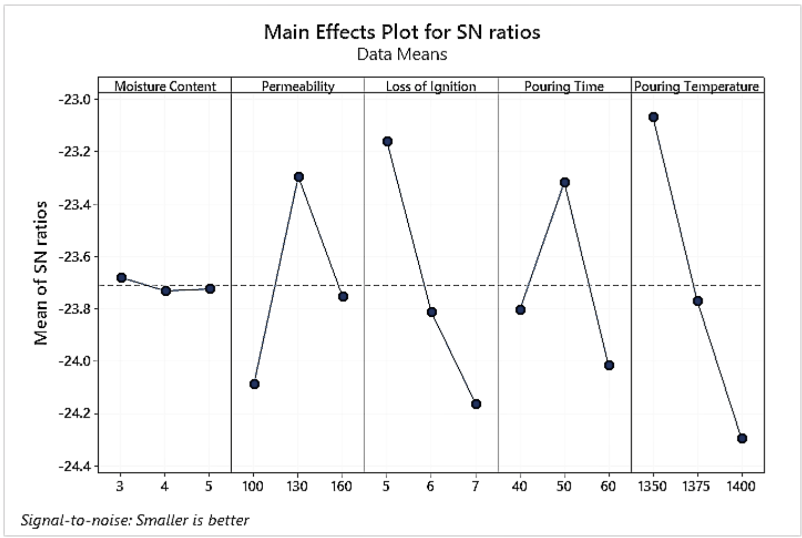

FIGURE 4. Main Effect Plot for Cracks

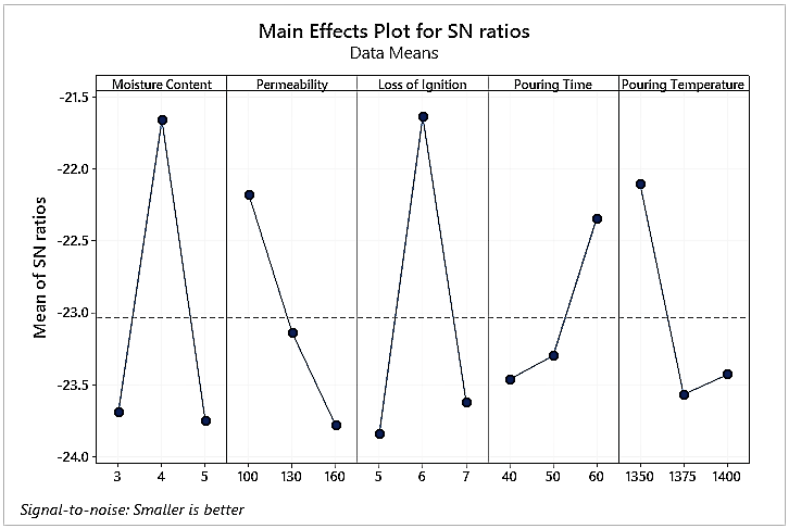

FIGURE 5. Main Effect Plot for Porosity

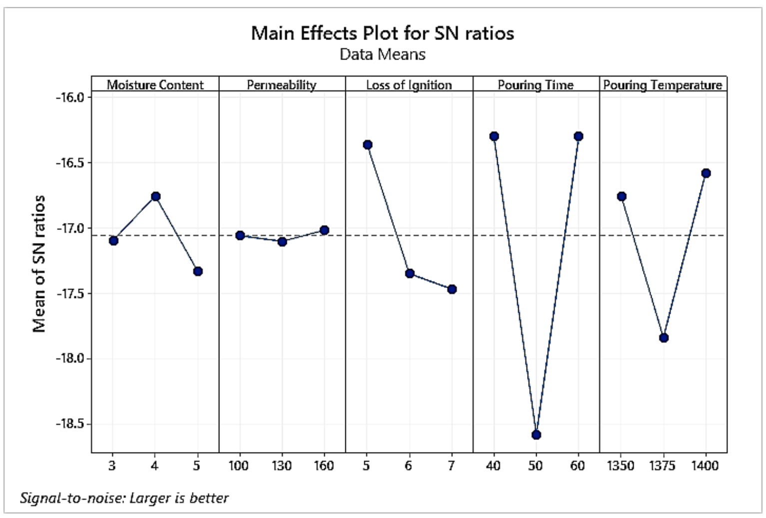

FIGURE 6. Main Effect Plot for PCA-GRG

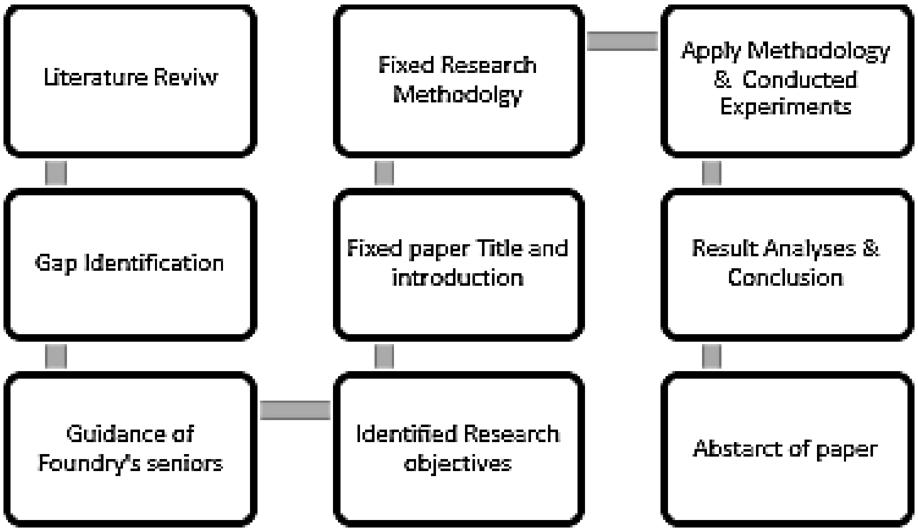

FIGURE 7. Mapping of Title, Abstract, Methodology & conclusion

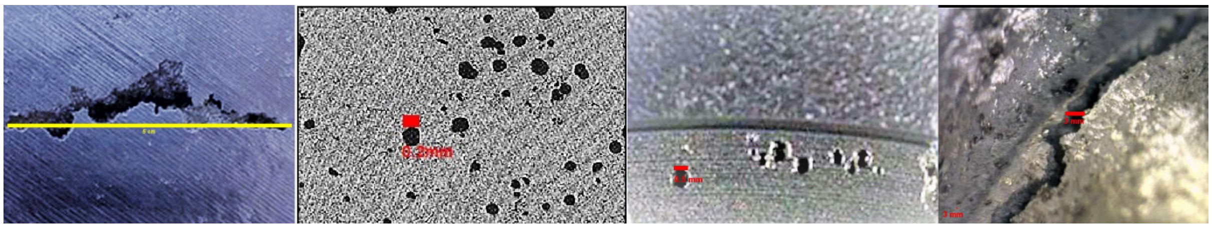

FIGURE 8 (a) Defect: Shrinkage, (b) Defect: Porosity, (c) Defect: Blow hole, (d) Defect: Crack

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DECLARATION OF COMPETING INTEREST

None.

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